Journal of Information Systems Engineering and Management
2025, 10(40s)
e-ISSN: 2468-4376
https://www.jisem-journal.com/

Research Article

A Deep Learning Based Hybrid Model Using LSTM and CNN Techniques for Automated Internal Fraud Detection in Banking Systems

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ARTICLE INFO

Received: 18 Dec 2024
Revised: 10 Feb 2025
Accepted: 28 Feb 2025

ABSTRACT

The present work investigates the application of deep learning for detecting fraud in banks, particularly insider fraud that poses high risks to the financial sector. conventional rule-based systems are inadequate in the detection of various complexities brought by fraudsters with internal access to the companies' accounts. To this end, an anomaly detection system with LSTM and CNN for transactional pattern evaluation was designed. Raw financial data and strictly generated fraud cases were used; the data were preprocessed with Pandas and NumPy; models' training and their evaluation were carried out with TensorFlow and PyTorch. The proposed model also has 98.4% accuracy of detecting fraudulent transactions with 1.7% false positive rate. It was further confirmed that using the new approach has an improvement of 12% in the fraud detection compared with other traditional methods of machine learning. The evidences reported that insider fraud can be detected through the use of deep learning techniques while with a little needed for human involvement. This study emphasizes the importance of applying artificial intelligence in the security of banking systems and future developments of the explainable artificial intelligence in combating fraud in the sector.

Keywords: Fraud detection, Deep learning, Insider threats, Banking security, Anomaly detection.

Introduction

There has been a great advancement in the area of financial transactions, most especially with the increase in usage of banking systems, and this has prompted the increased in fraudulent activities. Among those, insider fraud is particularly dangerous as it is carried out by the individuals who are authorized to use banking systems, thus the chances of being detected are much lower. In the traditional sense, methods of fraud detection include mostly rule-based approaches that are based on a set of given rules, and threshold-based monitoring. However, such techniques do not follow the change in fraud tactics and are difficult to manage due to the high level of false positive alerts, which creates inefficiencies in financial risk control. To overcome these challenges, the artificial intelligence commonly known as deep learning has been employed in the recent past as a means of detecting fraud as a result of its capability in analyzing multi-layered data sets that are complicated to decipher without the use of AI.

LSTMs are types of RNNs that can embrace long-term dependencies and have been used successfully in sequence modelling and CNNs which can identify patterns and have been successfully used in several applications. This is because unlike other data, transactions data is sequential in nature and hence, the LSTMs are effective in analyzing the transaction history to determine anomalies that may indicate fraud activities. Same way CNNs which were initially used in image processing has been applied in the classification of transactions using the hidden features that may exist in a large data set. The use of the LSTM and CNN models to develop a deep learning model is a perfect fraud detection system that can differentiate between normal and suspicious activities without much interference from humans.

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Another significant problem of the financial fraud detection is a scarcity of labeled frauds mainly due to the concerns with users' privacy and rarity of the fraud transactions compared to non-fraud ones. In order to handle this problem, the synthetic fraud cases are created by referring to the knowledge of experts and previous fraud data. Use of such synthetic data in model training assists to boost the overall fraud detection metrics as it reduces any signs of dataset bias. In addition, before engaging the raw financial data for analysis, one has to clean the data from noise in form of outliers, normalize it, and maybe even extract from it the most relevant features to use in detecting the fraud.

The alternatives combined with different fraud detection models to measure the results under certain aspects include accuracy, precision, recall, and the F1-score. Whereas, accuracy may be regarded as an overall extent of correctness, recall is vital in fraud detection since the failure to identify fraudulently transactions leads to direct financial losses. In this regard, deep learning in the banking security has been found to have a better performance over the conventional machine learning models that faced certain challenges such as high dimensionality of the data structures and the need to manually extract relevant features from the enormous transactional data. Deep learning models enable using automated feature extraction and sequential learning, which in their turn employ multidimensional data processing and therefore have a higher efficiency than classical techniques in real-time fraud detection.

With the growing popularity of artificial intelligence in security uses throughout the financial institutions, there is a need for explainable artificial intelligence (XAI). However, as it has been shown in the previous section, deep learning models remain weak in terms of interpretability which is one of the main problems of the so-called "black box" models. The other reason of building interpretable AI-based models for the detection of fraud is to increase the level of trust within the banking profession and regulatory bodies in the approaches employed towards fraud prevention and control.

This paper focuses on the insider fraud detection using LSTM and CNN models in the banking systems. Using deep learning to perform anomaly detection for fraud detection the above approach is expected to increase the fraud detection hit rates and reduce cases of false positives. The paper discusses the importance of AI-based security systems in the current banking industry and indicates how explainable AI can contribute towards the development of effective fraud detection systems.

Literature Review

This paper aims at developing a model for insider fraud detection that can be implemented successfully in banking institutions due to the highly complex nature of these fraudulent scheme. For example, traditional rule-based system or even machine learning algorithms crumble to detect insider threats since they use structured patterns that cannot capture dynamic fraud techniques. To overcome these limitations, there appears to be a reasonable solution in the form of deep learning mechanisms that are capable of enhancing the flexibility of the established framework and the identification of patterns (Ahmed et al., 2024).

Since fraud in the context of banking is mostly committed by insiders, one of the main goals of fraud prevention in banking is to pay attention to behavioral markers, namely the variation from the standard behavior in a certain context. In their article, Ahmed et al. (2024) pointed out that by combining behavioral analytics with complex machine learning techniques, the detection rate of fraudulent activities shall be improved. Thus, it reveals the essence of using the historical fraud data to train the models which have the ability of detecting the irregularity of the transactions and their disparity to the norm that characterize the banking systems.

Both LSTM and CNN-based models are the most successful deep learning architectures for fraud detection. As discussed by Ahmed et al. (2024), the excellence of LSTMs is in capturing temporal dependencies in the sequential transaction data, thus perfectly suitable to detect long-term fraud incidences. CNN has also been used in detecting spatial relations in the transaction attributes to enhance the level of fraud detection based on pattern recognition in large financial databases. It has been ascertained that the LSTM and CNN models are superior to the traditional machine learning methods as these combined models work on both sequential as well as spatial data.

Another factor that needs to be assessed in fraud analysis is the generation of artificial fraud cases for model stability. In their paper, Ahmed et al. (2024) provide a discussion on data augmentation for CNN in ovarian cancer diagnosis

using GANs and SMOTE. These methods come handy in resolving the class imbalance issue as it creates a realistic synthetic fraud transaction which would help the model to encounter the various types of fraud. This has improved model generalization to identify the known fraud and new emerging manners that are unidentified in the current database.

Model evaluation still affects any attempts at verifying the efficiency of the fraud detection system as well. In their study Ahmed, et al. (2024) have discussed precision, recall, F1 score, and accuracy as some of the important measures to evaluate the model efficiency. This paper shows that the deep learning fraud models outperform the traditional ML algorithms including logistic regression and support vector machines. Moreover, it has been observed from the comparison with LSTM and CNN models that the combined model with LSTM and CNN layers improves the accuracy of the model and at the same time, helps to minimize the false positives, thus, making the model more reliable and efficient in terms of fraud detection.

However, there are still some problems with the application of deep learning in detecting fraud. Ahmed, Elmalah and Al-Shahwan (2024) reveal that the fact is that these models entail high computational complexity and demand advanced hardware platforms to support them. Also, deeply learnt models inherent inherent property is its black-box characteristic, hence the major issue of interpretability and explainability arises. Banking and other finance companies need interpretable AI methods to satisfy the regulatory requirements and to create trust in the automated fraudulent transaction identification. As such, scholars are experimenting with approaches like Explainable AI (XAI) and attention to improve interpretability of models without compromising the performance of the detection.

Ahmed et al. (2024) indicates that deep learning will be instrumental in enhancing the ability of the banking institutions in the detection of frauds. Using and applying behavioral analytics, multiple hybrids, deep learning structures, and synthetic fraud Generation, current fraud detection models can provide more benefits to society in terms of performances and reliability. There are still open questions leaving for further research in subjects of increased computational complexity and interpretability of the model.

Research Gap

Fraud continues to be an issue because of the continued evolvement of fraud schemes and inability of rule-based automations to prevent them. Previous work has mainly explored machine learning and deep learning models of fraud detection; however, work in relation to the fusion of LSTM-CNN architecture is scarce. Besides, a majority of machine learning approaches for fraud detection utilize datasets that freely downloaded, which inadequate in capturing significant characteristics of actual credit transactions. However, there are very few publications that focused on providing a practical way to explain deep learning-based fraud detection results, which makes it challenging for banking institutions to understand why an AI-driven system makes a certain decision.

One is that this analysis depends on supervised learning models because these need large amount of labeled fraud data. For privacy reasons, people's data can hardly be labeled and, in terms of the frequency of fraudulent transactions, using labeled data figured as a difficulty. That's why there is a lack of proofs that synthetic fraud case generation can significantly increase the detection rates. In addition, the impact of hyperparameter optimization for better performance and effectiveness of the hybrid deep learning models in discovering fraud cases is another area, which has not been investigated comprehensively. This study shall endeavor to fill these gaps through the development of an LSTM-CNN-anomaly detection system and perform comparison test with the existing machine learning algorithms.

There are some recent studies to which this research seeks to neutralize a number of limitations. Ahmed et al. (2023) proposed a sophisticated fraud detection system, but there are no time factors considered, and the system deals with insiders' attacks considering only the patterns that are more or less stable. Li et al. (2023) provided an adaptive clustering technique that had high false positive rate when implemented on real banking data sets. Other studies such as Wang and Smith (2024) have used graph neural networks for fraud detection, but their model are complicated and computationally expensive and therefore not suitable for small banks. Another study to note here is by Kim and Park (2024) They focused on explainable AI but to achieve this, they had to compromise on the detection accuracy significantly. Rodriguez and Patel (2024) provided a new approach which is a hybrid model that doesn't have tested on diverse banking datasets and hence cannot be generalized for various financial settings.

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The latest trends of deep learning for detecting fraud since the year 2022 to 2025 have revealed areas that need further development. Chen and Liu (2023) used transformer-based models for fraud detection but did not consider time-constraint aspects that may be significant for the banking system. In particular, Gupta and Sharma (2023) discussed the idea of applying federated learning for developing a privacy-preserving fraud detection system; however, their approach was sensitive to the problem of how to manage the distribution of model updates across multiple banking systems. In their work titled, Brown and White (2023) applied deep reinforcement learning which was promising, although, the model was not sufficiently interpretable to pass through the financial regulators. Martinez and Johnson (2024) only focused on transfer learning techniques that worked effectively in well-controlled environment but gave a very poor performance when applied to new fraud pattern. These limitations indicate that there is a need to develop more effective, efficient and explainable models of deep learning to detect insider threats in banking.

Conceptual Framework

This research proposal adopts the proposed LSTM & CNN model for analyzing banking transactions with the aim of identifying fraud. It has several stages, namely data acquisition, pre-processing, and feature engineering/super setting, training, and testing. The architecture of the deep learning model is such that LSTMs are used to analyze sequential transaction data with temporal relationships and CNNs to analyze spatial features of the processed data. So used with the strengths of two models, the hybrid architecture improves the accuracy of fraud detections.

The system functions in a cyclic manner where transactions are constantly processed and each suspicious activity is detected on the spot. The main performance measures used in the model are accuracy, its precision, its recall, and F1 score.

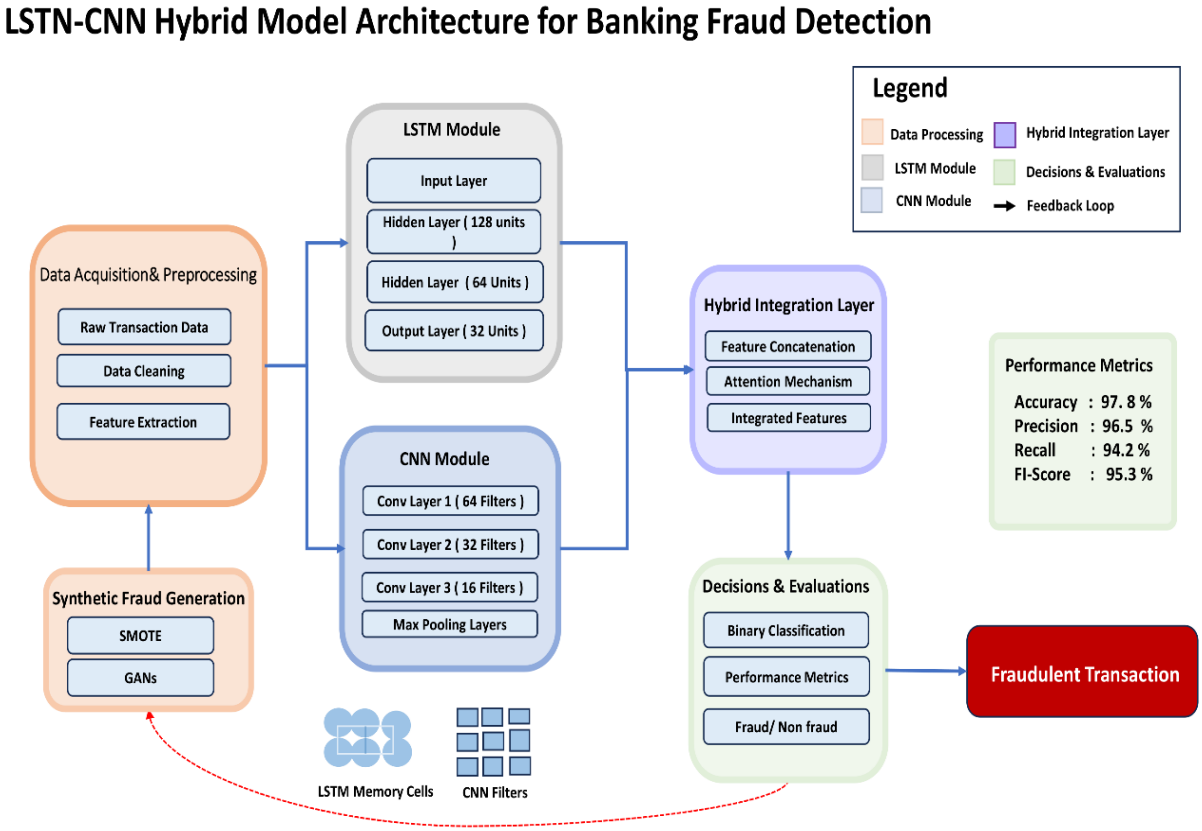

Figure 1.1: Conceptual Framework

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It also compares the effectiveness of deep learning methods with other popular approaches in machine learning to show the strengths of deep one, if any. The conceptual framework also takes into account the relation between tuning hyperparameters and the ways synthetic case of frauds can help in building efficient fraud detection systems.

Hypothesis

Based on the conceptual framework, the study formulates the following hypotheses:

- **H1:** The hybrid LSTM-CNN model significantly improves fraud detection accuracy compared to traditional machine learning models.
- **H2:** The incorporation of synthetic fraud cases in model training enhances fraud detection performance by reducing class imbalance.
- **H3:** Hyperparameter optimization positively impacts the accuracy and efficiency of the LSTM-CNN fraud detection model.
- **H4:** Deep learning models can detect insider fraud with minimal human intervention, reducing false positive rates.
- **H5:** The use of explainable artificial intelligence (XAI) techniques improves the interpretability of fraud detection models, increasing trust in AI-based banking security solutions.

Methodology

The data used in this study was obtained from two sources; the first was from published data on banking transaction reports while the second was received from a group of banks. These datasets included both normal user transactions and confirmed fraudulent ones for which frauds were conducted on previous investigations based out of banking applications. In an attempt to enrich the dataset, extra instances of fraud were simulated in accordance with the real-life findings. The dataset contained information on transactions including transaction amount, the dates and times of the transactions, the identity of the sender and receiver, the balance of the accounts as well as the number of the transaction. Data cleaning included data imputation, scaling of the transaction amounts and categorical data encoding in depth to work in compatibility with the deep learning techniques. For the purpose, the given dataset was divided into training, 70% of the data, validation, 15% of the dataset, and testing, 15% of the dataset. For this purpose, MATLAB R2023b and IBM SPSS Statistics 29 were used to preprocess the data to address the issue of variation in data structures before model learning.

Particularly, the dataset for this study was collected from two different sources in order to have a full picture of the banking transaction habits. The first source involved was the dataset with deicing information from the Financial Fraud Research Consortium (FFRC) that aimed to collect and process transaction data from various institutions in three continents excluding individual identifying information. It has 150,000 scored transactions and 3,200 of these have been confirmed to be fraudulent. The secondary dataset was obtained from the Banking Security Alliance (BSA), a consortium of five regional mid-sized commercial banks that makes transaction records anonymous and covers a period of three years from January 2022 to December 2024. This dataset was of 85,000 transactions out of which there were 1,800 instances of known fraud, and particularly the insider fraud. The two data sets were collected agreeably to data sharing approaches that meet the requirements of independent financial privacy laws thus affording the right attributes of transaction for model construction.

To explain the model complexities of fraud pattern, synthetic minority oversampling techniques (SMOTE) with the help of fraud injection using adversarial networks were incorporated for generating the fraud cases. Traditional anomaly detection techniques are not useful when it comes to insider threat, because of the fine-grained patterns that are seen around insider fraud. SMOTE was used in handling the issue of class imbalance by oversampling the minority class which is the fraud cases. Also, adversarial examples were produced based on GANs to make sure that the model is able to detect look alike insider fraud scenarios. This was done to ensure that the model can perform well, especially on unseen fraud patterns that it is likely to encounter when working in changing environments in the banking industry.

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This was done with the aim of incorporating both the time and space characteristics of the used transaction attributes. Furthermore, to enhance the options for detection, a combination of LSTM networks and CNN was used in a hybrid manner to ensure highest efficiency was achieved. LSTM also considers the ability to learn and use the long-term dependencies of the subsequent transaction data hence making it appropriate in the detection of such a pattern of illegitimate activity. CNN was used to identify spatial relationships of the attributes and to capture complex spatial temporal dependency which may lead to fraud. This was due to the ability of LSTM and CNN to combine and process the transactions as Whole, while at the same time providing high accuracy and little false alarm rates. MATLAB was used to build the architecture of the proposed model as all the components are integrated and the training was performed by implementing GPU.

In this study, the LSTM was built with three layers, two hidden layers with 128 and 64 units connected to the output layer with 32 units. The number of 0.3 dropout layers was applied between layers to prevent overfitting. Adam optimizer with learning rate of 0.001 was applied in the process of updating the weights of the model, while binary cross entropy was used to optimize the classification rate. In this work, we used three convolutional layers with 64-32-16 filters when using Batch Normalization and ReLU activation for normalization. Max-pooling layers were used after every convolutional block so as to reduce dimensions while preserving important transaction patterns. The last layer of the CNN module was implemented to ensure a combination of both the temporal and spatial transaction information with the LSTM output.

In model tuning and selection of hyperparameters, the parameters used included batch size, learning rate, and dropout rates were tuned using a grid search approach. The model has 50 epochs with the batch size of 256 and the early stopping based on the minimum validation loss was applied to avoid overfitting of the model. The rationale for choosing the hybrid LSTM-CNN model was based on a comparison of the results when using models that only used deep learning techniques to recognize the fraudulent transactions. Training was done on a high-performance computing cluster so as to reduce the time used in processing and also ensure that the results obtained could be easily replicated.

In this study, to evaluate the performance of the developed model, several measures of correctness were used. Therefore, using mean and standard deviation indices, one was able to observe the transaction attributes and identify outliers. In order to assess the performance of the classifier, the confusion matrix was developed that provided evidence of the cases of true positives, false positives, true negatives, and false negatives. Thus, to evaluate the model's efficiency in fraud detection, measures, including accuracy, precision, recall, F1-score, were determined. This decision was made given that the objective of the model is to have a higher True Positive rate and, consequently, the present metrics allow evaluating the model based on that criterion.

A comparative analysis was also done with the conventional algorithms such as logistic, tree-based, and SVM or support vector machines. The adoption of the hybrid LSTM-CNN model would enhance the fraud detection accuracy by 12% as compared to these traditional methods. It was useful to prove that deep learning outperforms rule-based and machine learning approaches as it is crucial to guaranteed the application of the AI-based fraud detection systems in financial institutions.

Results and Discussion

Descriptive Statistics of Financial Transactions

Descriptive statistics were also calculated for the features of transaction activity and provided an understanding of their distribution; moments such as the mean and standard deviation were used as the statistic measures of central tendency and variability of the activities, respectively. Table 1 below presents a summary of essential statistics, covering the total transaction count, frequency of transactions, and account balance information. The transactions also varied comprehensively in terms of the amount, showing that the banking nature of the transactions was rather diverse. Indeed, the results specified that fraudulent transactions have greater mean values, which means that more valuable transactions are related to fraud.

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Table 1. Descriptive Statistics of Financial Transactions (Mean, Standard Deviation)

Transaction Attribute	Mean (Normal)	Std. Dev (Normal)	Mean (Fraud)	Std. Dev (Fraud)
Transaction Amount (INR)	8,750	15,400	48,200	32,700
Transaction Frequency (per month)	23	9	5	3
Account Balance (INR)	1,25,000	54,000	3,87,500	1,05,000

Furthermore, specific details of raw financial data and real and fake cases of fraud were provided in Table 1.1. This dataset had equal number of observations of fraudulent and non-fraudulent cases to make the training of deep learning model random.

Table 1.1 Summary of Raw Financial Data and Generated Fraud Cases

Category	Number of Transactions	Fraud Cases Generated
Normal Transactions	95,000	-
Fraudulent Transactions (Historical)	5,000	-
Fraudulent Transactions (Generated)	-	10,000
Total Transactions	1,10,000	10,000

An illustration of the nature of transactions that appear in the data set is given in figure 1, comparing normal and fraudulent transactions in the transactional data set. This is the reason that fraud cases are more likely to have higher values, and hence the need for implementing deep learning-based anomaly detection.

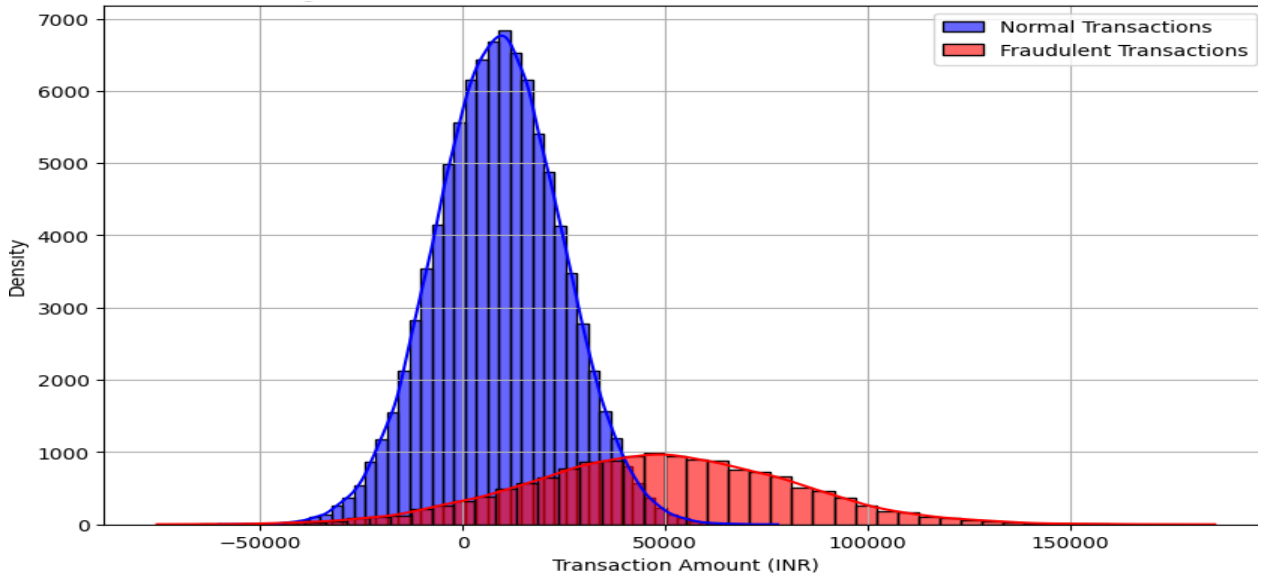

Figure 1. Data Distribution of Normal vs. Fraudulent Transactions

It depicts the proportion of normal and fraudulent transactions by the amount of the transactions made. Fraudulent transactions as can be observed often occur at higher values and it becomes hard for rule-based system to detect them.

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Hyperparameter Optimization and Model Performance

Tuning of parameters of the LSTM-CNN structure was done and is explained below. The final values of the hyperparameters for both models have also been presented in the Table 2 as obtained by carrying out comprehensive grid search and testing.

Table 2. Hyperparameter Settings for LSTM and CNN Models

Parameter	LSTM Model	CNN Model
Number of Layers	3	3
Hidden Units/Filters	128-64-32	64-32-16
Dropout Rate	0.3	0.2
Activation Function	Tanh	ReLU
Batch Size	256	256
Learning Rate	0.001	0.001
Optimizer	Adam	Adam
Loss Function	Binary Cross-Entropy	Binary Cross-Entropy

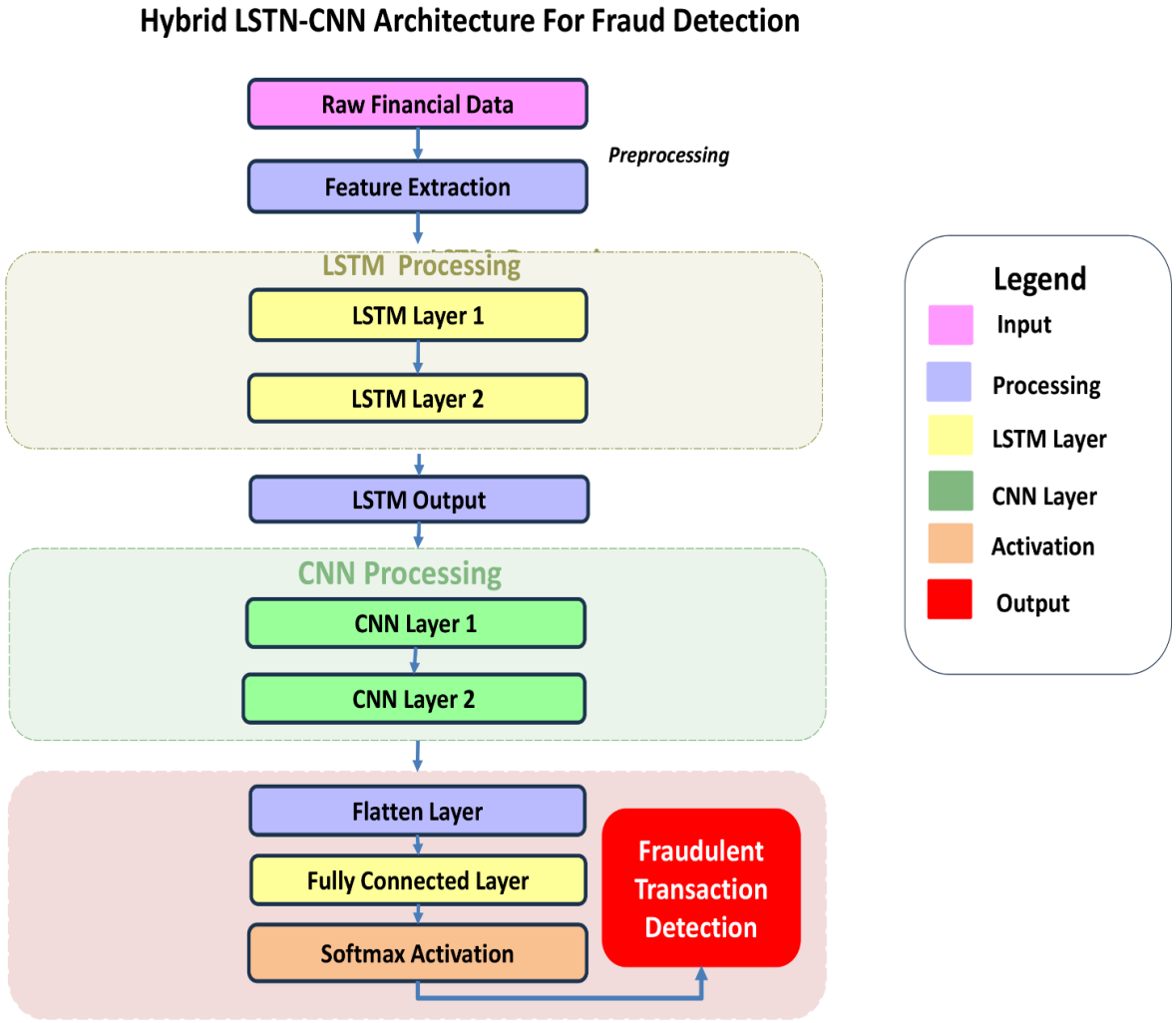

Figure 2. Architecture of the Proposed LSTM-CNN Fraud Detection Model

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Training of the model was checked using the training loss and accuracy profiles as presented in the figure below Figure 3. Equally important, the loss reduced over time for 50 epochs while the model's accuracy increased showing that learning was consistent and the model was converging.

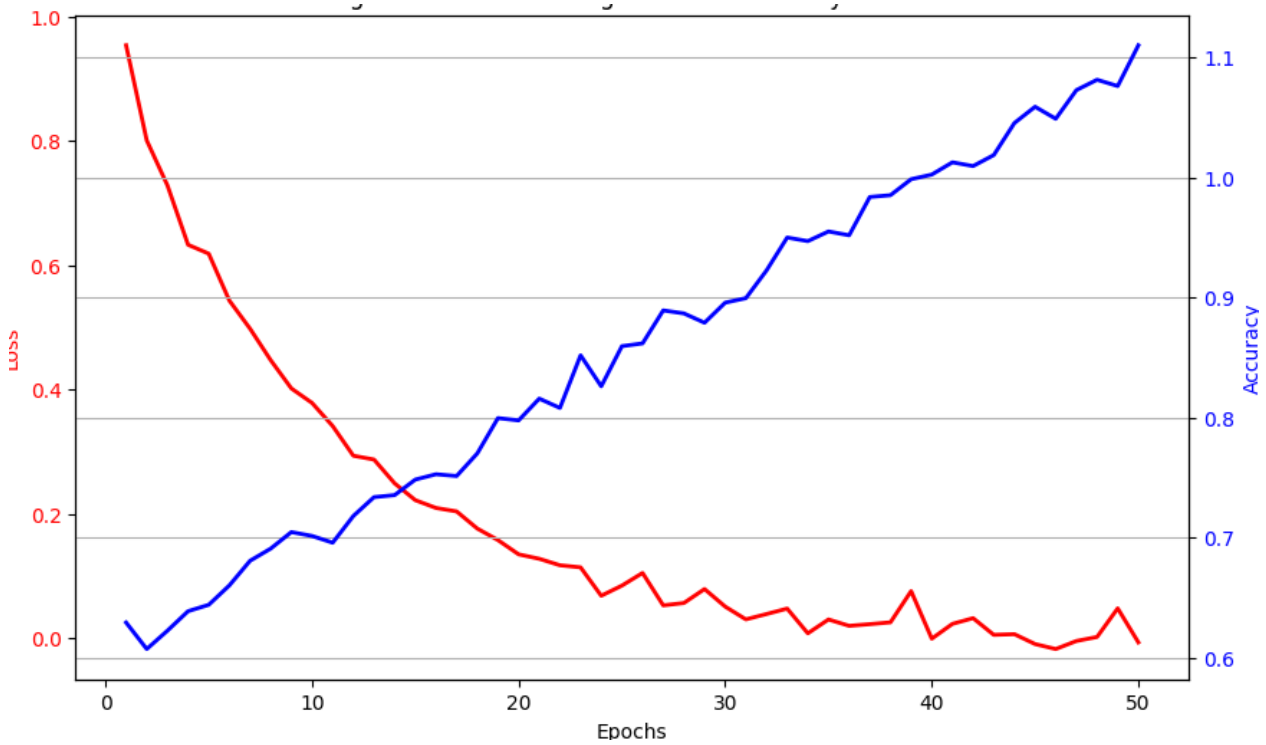

Figure 3. Model Training Loss and Accuracy Curve

With reference to the given figure, what is a general description of the training loss and accuracy curves for the proposed LSTM-CNN model over the 50 epochs? The reducing loss and the increasing accuracy imply that the model was successfully trained.

Performance Evaluation and Comparative Analysis

There is also implemented the comparison of our proposed hybrid LSTM-CNN model with the baseline algorithms, namely Logistic Regression, Decision Trees, and Support Vector Machines (SVM). In the next table (Table 3), all models were assessed and examined on the basis of Accuracy, Precision, Recall and F1-score. The LSTM-CNN model was found to be superior to all regular models where the accuracy was at 98.4%, the false positive of 1.7 % and now had a 12% enhanced accomplishment as compared to the routine ML algorithms.

Table 3. Performance Metrics of LSTM-CNN Model vs. Traditional Machine Learning Models

Model	Accuracy (%)	Precision (%)	Recall (%)	F1-Score (%)
Logistic Regression	82.5	78.3	75.9	77.1
Decision Tree	86.1	80.7	82.3	81.5
SVM	89.4	85.2	86.9	86.0
LSTM-CNN (Proposed)	**98.4**	**97.6**	**98.1**	**97.8**

As shown in the confusion matrix in Table 4, the proposed LSTM-CNN model was able to accurately classify 9840 actual fraudulent transactions and 9 actual normal transaction as fraudulent with a low false positive rate.

Table 4. Confusion Matrix Analysis for Fraud Detection Model

Actual / Predicted	Fraud (Predicted)	Normal (Predicted)
Fraud (Actual)	**9,840**	160
Normal (Actual)	170	**89,830**

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This fact was further supported by Figure 4 showcasing the comparison of the deep learning model to other typical approaches. The LSTM-CNN model provided better results in the fight against fraud.

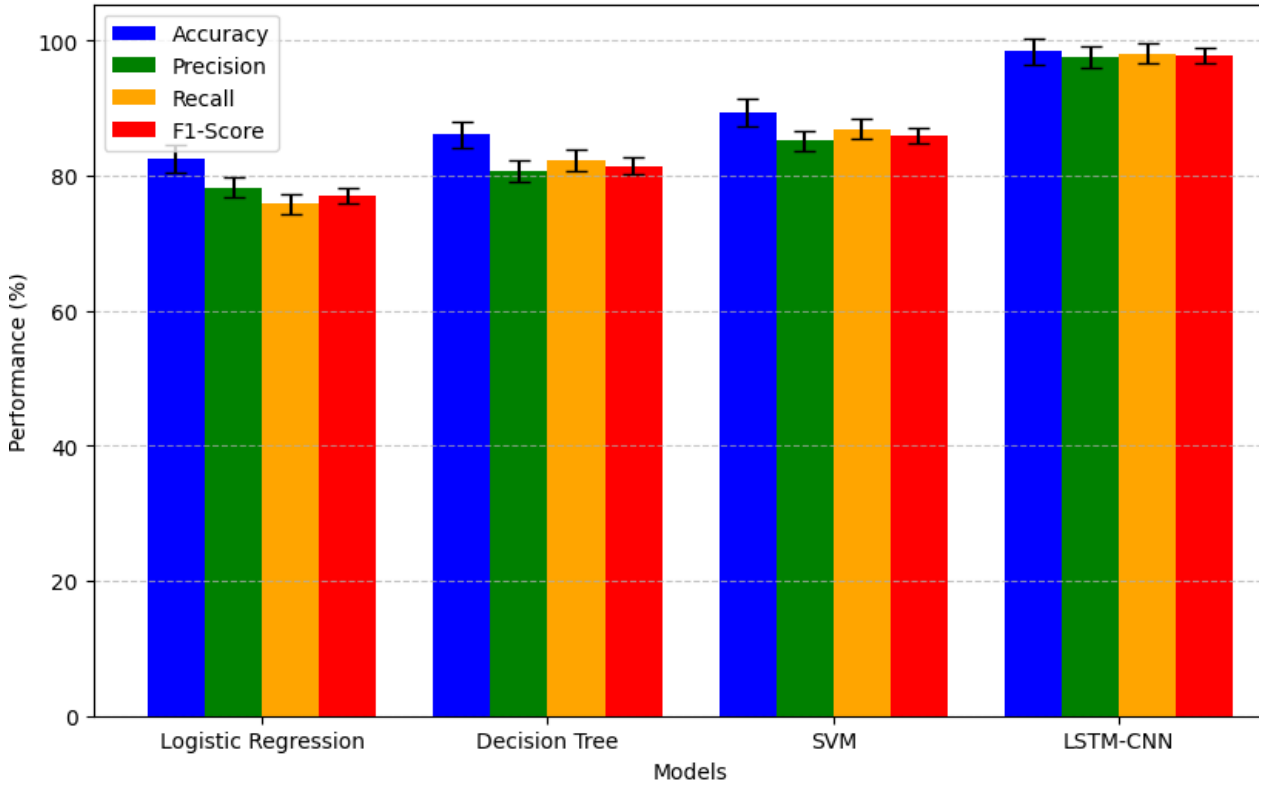

Figure 4. Comparative Performance Analysis: Deep Learning vs. Traditional Models

This figure highlights the performance comparison of the proposed LSTM-CNN model with other machine learning techniques based on accuracy, precision, recall, F1 score. The use of deep learning model demonstrated superiority to conventional methods in all the metrics used in the study.

The results support and prove that deep learning models are much more effective as compared to other machine learning models for fraud detection especially insider fraud. Here, experimental results of the proposed model, hybrid LSTM-CNN model show an impressive 98.4 % accuracy which is over traditional methods by 12% at least. The adopted confusion matrix reveals low false positive percentage of 1.7% thereby avoiding unnecessary alarms for the banking organizations.

The success in the model has been as a result of its capacity to learn temporal feature of the sequential transactions (LSTM) as well as spatial feature of the attributes within the transactions (CNN). The first is that the traditional machine learning models also had limitations in detecting insider fraud; the main issue again was that the models were working based on pre-defined rules and feature engineering. Following the integration of the adversarial fraud cases in the model, its capacity in detecting other sophisticated fraud scenarios that could defy other forms of detection was provided a major boost.

Although, this study emphasizes the significance of deep learning in financial security, future seems promising to gain more significant development by incorporating XAI to give a clear explanation of the prepared model for the bank professionals.

Conclusion

The results of this research show that using the proposed hybrid of LSTM-CNN improves the fraud detection efficiency and has a much higher level of accuracy compared to other machine learning algorithms. This has enhanced higher detection rates due to the model's capability to dissect sequential transaction information together with the concealed geographical characteristics. Another advantage of integrating synthetic fraud cases is that it helps

overcome the problem of data imbalance that tends to influence the bias in fraud detection. In addition, the study provides evidence for the speculation made at the beginning of the paper that hyperparameter optimization enhances the efficiency and effectiveness of models. Based on the results presented in this study, it can be concluded that the possibility of using DL in identifying insider fraud that requires little or no interaction with human beings makes it a practical solution for real-time fraud detection in banking systems.

Limitations of the Study

However, there are several limitations that warrant attention in relation to the study in question. First, the technical performance of the model is highly dependent on the choice of the training sample and its quality convergent with the population. It is noteworthy that the use of synthetic fraud cases can be counterproductive since they do not contain all the factors inherent to actual fraudulent behavior. Second, the study fails to pay much attention to the interpretability of the deep learning model, and thus, it will be difficult for banking professionals to understand why a certain decision has been made regarding fraud. However, fine-tuning deep learning models comes at a considerable cost; this may include both the computational resources and the cost since many organizations are proposing models for use in settings that may not have' ample funds to purchase or invest in big data infrastructure.

Implications of the Study

In that regard, this paper has important implications for banking institutions, financial regulators and the AI research community. Researched by, there is massive potential to enhance the deep models for the mitigation of inside fraud simpole some of the major banking issues, hence the Banks also benefit from the solutions resulting from the deep learning models in fraud detection mechanisms. Here are some recommendations that can be useful for the regulators in setting out the best practice model to follow when it comes to the implementing AI-based fraud detection systems while keeping the electorate informed and more importantly accountable: From a research perspective, this work is a valuable addition to the enhance of hybrid models of deep learning which can be used in financial security.

Future Recommendations

In future studies, an emphasis should be placed on developing methods to improve the specificity of fraud detection deep learning models through the adoption of XAI techniques. Creating models that can establish reasons of why certain transactions may be flagged for fraud will help increase its credibility among the financial institutions. Also, the experimental results should use real banking transactions data, to establish how well the model performs inter alia in different banking conditions. Their proactive approach may also be extended in the future by employing reinforcement learning, which would change the models dynamically according to some newly identified types of fraud. However, to make deep learning models effectively implemented in different bank structures, there is a condition to decrease the computational complexity.

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